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Authors' Affiliation:
[1]Medical University of Silesia, Poniatowskiego 15, 40-055 Katowice, Poland
[2]Wojewodzki Szpital Specjalistyczny nr 5 w Sosnowcu, Plac Medykow 1, 41-200 Sosnowiec, Poland

Orcid list:

Anna Mazur:	0009-0007-3433-4550
Julia Brodziak:	0009-0000-3332-9919
Wiktoria Ciszewska:	0009-0008-9090-9715
Michał Dworak:	0009-0006-9771-0421
Katarzyna Fojcik:	0009-0000-5249-8398
Zofia Kosztyła-Czech:	0009-0001-0839-4476
Marta Kowalska:	0009-0001-1397-9102
Mateusz Matyja:	0009-0001-8928-0170
Wiktor Werenkowicz:	0009-0008-8487-2426
Tomasz Wiśniewski:	0009-0001-7919-8309

***Corresponding author:**
Anna Mazur,
Medical University of Silesia, Poniatowskiego 15, 40-055 Katowice, Poland,
Tel: +48 665 799 606
Email: ankat.mazur@gmail.com

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AI-driven interpretation of electrocardiograms in the diagnosis of common cardiovascular disorders: a systematic review

Anna Mazur[1]*, Julia Brodziak[1], Wiktoria Ciszewska[1], Michał Dworak[1], Katarzyna Fojcik[1], Zofia Kosztyła-Czech[1], Marta Kowalska[1], Mateusz Matyja[2], Wiktor Werenkowicz[1], Tomasz Wiśniewski[1]

ABSTRACT

Electrocardiography (ECG) is widely used in everyday cardiology practice, but its interpretation can be difficult, especially when electrical abnormalities are mild or atypical. Artificial intelligence (AI) has become an important tool in ECG interpretation over the past 10 years. These methods can improve the detection of arrhythmias, ischemia, heart failure, and structural heart diseases. In this article, we review studies that analyzed how AI can support ECG-based diagnosis across a range of common cardiovascular (CV) conditions. We identified 26 articles that met the inclusion criteria. Most of the included studies relied on deep learning approaches. Their performance was encouraging, especially in detecting atrial fibrillation (AF), myocardial infarction (MI), left ventricular dysfunction, and various cardiomyopathies. New research also supports the use of artificial intelligence-assisted ECGs for detecting pulmonary hypertension, treatment-related cardiotoxicity, cardiovascular risk estimation, and predicting diastolic dysfunction. A major obstacle is that scientists trained many models on retrospective datasets from a single center. Only a few of them underwent robust external validation. Despite this, AI-ECGs may help clinicians in everyday work. In the future, research should involve larger, more diverse patient groups, standardized reporting standards, and prospective validation studies. These steps are necessary to understand whether AI-ECG tools can improve clinical outcomes.

Keywords: artificial intelligence; electrocardiogram; deep learning; cardiovascular diseases; arrhythmia

1. INTRODUCTION

Heart diseases are the leading cause of death worldwide, and early diagnosis is the most important for improving patient outcomes (Feeny et al., 2020). The electrocardiogram is a simple, affordable test that is available in every hospital or ambulatory setting. Clinicians use it to evaluate rhythm disturbances, ischemia, conduction problems, or any other indirect signs of structural heart disease, but interpreting an ECG may still be challenging. Doctors have different levels of knowledge and skills, and standard automated ECG systems are often unable to detect more complex or subtle problems (Nagarajan et al., 2021; Siontis et al., 2021). Many of these modern artificial intelligence (AI) models work directly on raw waveforms and can highlight patterns that clinicians may overlook (Hannun et al., 2019; Attia et al., 2019). As a result, there has been a rapid increase in studies that explored applications where ECG is supported by AI for conditions like atrial fibrillation, ischemia, heart failure, pulmonary hypertension, cardiomyopathies, and even in monitoring treatment-related cardiotoxicity (Jabbour et al., 2024; Lee et al., 2025; Chou et al., 2024; DuBrock et al., 2024; Poterucha et al., 2025; Shaffer et al., 2024). Although several reviews have discussed aspects of AI in cardiology, few have focused specifically on its role in ECG interpretation across the common cardiovascular conditions. An updated summary is therefore needed (Siontis et al., 2021; Kashou et al., 2022). In this article, we brought together recent studies to provide an updated overview. Scientists are now using AI-based ECG models to detect diseases, estimate cardiovascular risk, and predict mortality. These results suggest that ECGs can help with diagnosis and long-term risk assessment (Sau et al., 2024; Jentzer et al., 2025).

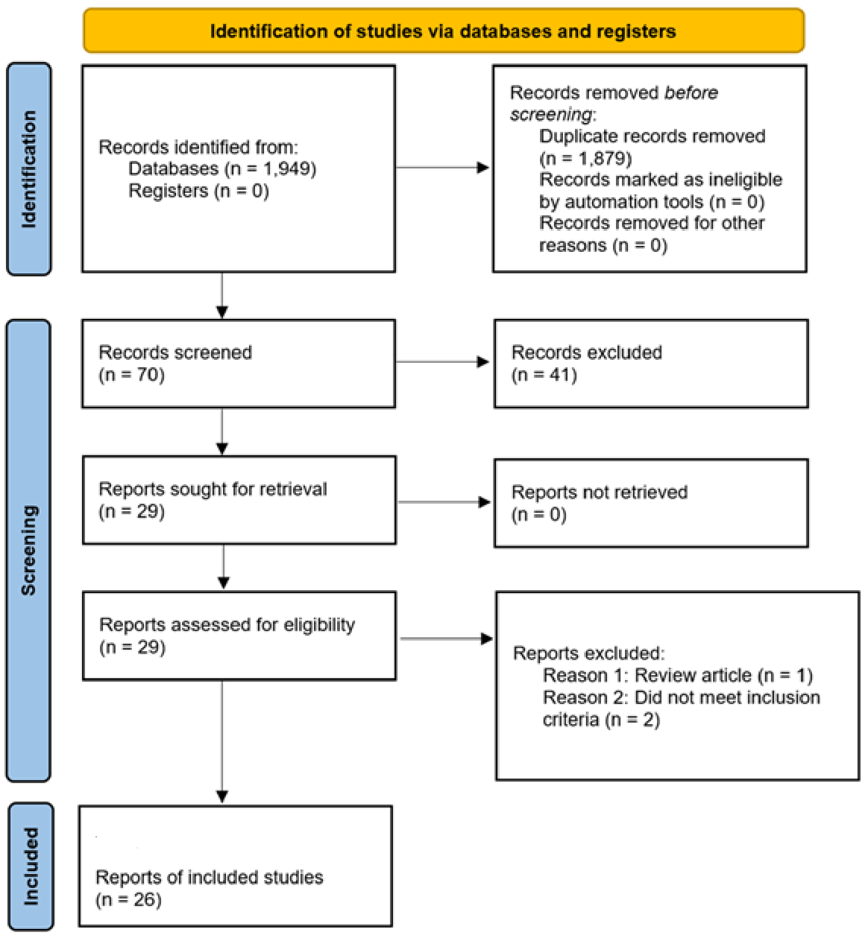

Figure 1. PRISMA flow diagram of study selection.

2. REVIEW METHODS

For this review, we used the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) guidelines. We included studies that applied AI techniques to ECG recordings for diagnosis or prognosis. We searched PubMed up to the 31st of August 2025. We used terms: “clinical applications of artificial intelligence in ECG diagnostics” and “artificial intelligence in ECG diagnostics”. We filtered results by publication date (January, 2015 – August, 2025) and free full text. Our search identified 1,949 records. After we removed duplicates, we screened 70 titles and abstracts. Of these, 41 records we judged as irrelevant, and 29 full-text articles we reviewed for eligibility. Three full-text articles were excluded (one review article and two studies not meeting the predefined inclusion criteria). We searched through articles including human ECG recordings in which AI, machine learning, or deep learning methods were applied directly to ECG waveforms. Our target conditions were common cardiovascular disorders (arrhythmia, ischemia/MI, heart failure, structural heart disease, pulmonary hypertension, cardiotoxicity) and also other AI-driven ECG features relevant to cardiovascular risk (e.g., ECG-based estimates of age, sex, or "physiologic age"). We required studies to share results about how well their tests worked and to be original research articles or systematic or narrative reviews. We excluded studies based on traditional ECG analysis without AI, those focused on ECG preprocessing only, case reports, editorials, commentaries, applications not related to cardiovascular diseases, and non-English-language articles. Studies included in the qualitative synthesis are 26. The PRISMA diagram shows the article selection process (Figure 1). Because the studies were highly diverse, we grouped the results by clinical category and summarized them narratively.

3. RESULTS & DISCUSSION

The 26 included articles discussed a range of AI-ECG applications. That demonstrates how quickly this field has grown over the past few years (Feeny et al., 2020; Siontis et al., 2021). The articles included models to detect arrhythmias (Hannun et al., 2019; Chang et al., 2022; Wu et al., 2021; Jabbour et al., 2024; Schoels et al., 2025), ischemia and myocardial infarction (Goto et al., 2019; Lee et al., 2025; Dali et al., 2025; Muzammil et al., 2024) and pulmonary hypertension (DuBrock et al., 2024). They also discussed algorithms that predict heart failure or structural abnormalities (Chou et al., 2024; Cho et al., 2024; Poterucha et al., 2025), as well as those to assess cardiotoxicity in oncology and transplant patients (Shaffer et al., 2024). In addition, they reviewed broader applications of AI-ECG (Siontis et al., 2021; Feeny et al., 2020; Kashou et al., 2022). Most studies were retrospective and were based on datasets from a single center. Only a few studies included any form of external validation (Nagarajan et al., 2021; Sau et al., 2024). The characteristics of the included studies are presented in a table (Table 1).

Table 1. Characteristics of studies included in the review

Author (year)	**Study design & setting**	**Population**	**ECG type**	**AI approach**	**Target condition**	**Main finding**
Hannun et al. (2019)	Retrospective ambulatory monitoring study	Adults using wearable ECG monitors	Single-lead ECG	Deep neural network	Arrhythmias	AI achieved cardiologist-level performance for the detection of multiple arrhythmias.
Wu et al. (2021)	Retrospective model development and validation	Adults with and without atrial fibrillation	12-lead ECG	Ensemble machine learning	Atrial fibrillation prediction	AI-enabled early identification of individuals at risk of future AF.
Chang et al. (2022)	Retrospective diagnostic study	Patients with ventricular premature complexes (VPC) and controls	12-lead ECG	Convolutional neural networks	Ventricular premature complexes	AI identified individuals with VPC using sinus rhythm ECGs.
Lee et al. (2025)	Multicentre emergency department cohort	Patients with suspected acute coronary syndrome	12-lead ECG	Deep learning–based AI-ECG score	Acute myocardial infarction	AI-ECG showed strong performance for AMI detection and risk stratification.
Poterucha et al. (2025)	Multicentre development and validation study	Adults without prior cardiac imaging	12-lead ECG	Deep learning model	Structural heart disease	AI-ECG detected multiple structural heart diseases from standard ECGs.
DuBrock et al. (2024)	Retrospective development and external validation	Clinical ECG databases	12-lead ECG	Convolutional neural network	Pulmonary hypertension	AI-ECG detected pulmonary hypertension, including years before clinical diagnosis.

Attia et al. (2019)	Retrospective development and validation study	Large health-system population	12-lead ECG	Convolutional neural network	Age and sex estimation	AI predicted biological sex and physiologic age from ECGs.
Jentzer et al. (2025)	Historical CICU (cardiac intensive care unit) cohort study.	Critically ill cardiac patients.	12-lead ECG	AI-ECG algorithm.	Diastolic dysfunction.	AI-derived diastolic dysfunction was associated with increased mortality.
Cho et al. (2024)	Prospective registry-based study	Patients with acute heart failure	ECG images	Deep learning model	Mortality prediction	AI-ECG predicted in-hospital and long-term mortality.
Shaffer et al. (2024)	Retrospective cohort study	Hematopoietic cell transplant recipients	ECG images	Deep learning model	Cardiotoxicity / atrial fibrillation risk	AI-ECG predicted post-transplant AF and adverse outcomes.
Schoels et al. (2025)	Retrospective derivation and validation study	Acute ischemic stroke patients	Single-lead ECG	Ensemble learning	Occult atrial fibrillation	AI improved detection of previously unrecognized AF.
Chou et al. (2024)	Multicentre retrospective development and validation	Adults with paired ECG and echocardiography	12-lead ECG and single-lead leads I/V2	Convolutional neural networks	Left atrial enlargement	AI-ECG detected left atrial enlargement and predicted future cardiovascular events.
Sau et al. (2024)	Multinational development and validation study	Community and clinical populations	12-lead and single-lead ECG	Deep learning survival model	Cardiovascular risk prediction	AI-ECG predicted mortality and major cardiovascular events.

Arrhythmias

Atrial fibrillation was the most frequently studied arrhythmia. Multiple studies that used both standard 12-lead and simple single-lead ECG data, deep learning models performed very well, with high sensitivity and specificity (Hannun et al., 2019; Chang et al., 2022; Wu et al., 2021; Jabbour et al., 2024; Schoels et al., 2025). In some studies, researchers have found that artificial intelligence can help find patients with paroxysmal AF even when their ECG looks normal. It can be hard to find these cases using standard ECG interpretation (Attia et al., 2019; Jabbour et al., 2024). In many studies, AI models did better than standard computer ECG programs (Feeny et al., 2020; Nagarajan et al., 2021; Hannun et al., 2019). At the same time, the ways of checking the results were different, and models trained in one healthcare system often did not work as well in other groups (Siontis et al., 2021; Sau et al., 2024).

Ischemia and myocardial infarction

Researches have studied how AI can help clinicians better detect acute coronary syndromes. AI models trained on 12-lead ECGs in emergency or prehospital conditions were more accurately at finding small signs of ischemia than traditional systems (Goto et al., 2019; Lee et al., 2025; Muzammil et al., 2024). The findings suggest that using AI to interpret ECGs could help doctors make faster decisions and shorten the time from admission to make the correct diagnosis. Research also shows that AI-ECG can detect occlusion myocardial infarction (OMI), even when the usual ST-segment elevation criteria are not met. It can also lower the number of false-positive ST-segment elevation myocardial infarction (STEMI) activations (Lee et al., 2025; Dali et al., 2025). Putting these results together indicates that AI might improve ischemia detection and also decisions related to triage or catheterization lab activation (Muzammil et al., 2024; Lee et al., 2025). Direct comparisons between studies are difficult because they use different reference standards, from angiography to troponin testing or clinical judgement (Muzammil et al., 2024; Sau et al., 2024). Prospective studies conducted in real-world clinical settings are still uncommon (Siontis et al., 2021; Feeny et al., 2020).

Heart failure and structural heart disease

Using artificial intelligence to look at regular ECGs has made it easier to detect systolic dysfunction in the left ventricle. In studies where researches used both ECG and echocardiography data showed that these models can detect reduced ejection fraction (EF) even when the ECG appeared normal to physicians (Cho et al., 2024; Poterucha et al., 2025; Siontis et al., 2021). These findings suggest the possibility of using AI-ECG as a screening test in primary care or emergency departments (Siontis et al., 2021; Nagarajan et al., 2021). Researchers used AI models to help detect cardiomyopathies, enlarged heart chambers, and conduction disorders (Adedinsewo et al., 2024; Chou et al., 2024; Muzammil et al., 2024). Overall performance was good, although how well the studies explained how the models were adjusted and how easy they were to understand was different from study to study (Feeny et al., 2020; Kashou et al., 2022). Several studies have used similar methods to assess diastolic dysfunction and an enlarged left atrium. They imply that AI-ECGs can detect early or subtle signs of structural changes. These problems may cause negative outcomes and may not be visible to a physician's eye (Jentzer et al., 2025; Chou et al., 2024). Some of the latest models of structural heart disease include specific approaches to the analysis of P-wave morphology, suggesting that future AI-ECG methods may rely more on atrial electrophysiology rather than on ventricular patterns (Chou et al., 2024; Wu et al., 2021).

Pulmonary hypertension and cardiotoxicity

In some studies, researchers used artificial intelligence to identify high blood pressure in the pulmonary artery and different types of pulmonary hypertension. Compared with heart ultrasound and more involved tests like right heart catheterization, these AI programs worked very well (DuBrock et al., 2024; Ferreira, 2023; Muzammil et al., 2024).

AI-based ECG analysis has also been studied in oncology and transplant patients to find early signs of treatment-related cardiotoxicity. Early research in this area shows that using deep-learning ECG markers might help find patients at higher risk of complications after hematopoietic cell transplantation (Shaffer et al., 2024). Although these applications are still in early stages of development, they suggest that AI-ECG could be useful beyond standard arrhythmia or ischemia detection, offering support for broader clinical decision-making in a range of patient populations.

Other AI-ECG applications: cardiovascular risk and diastolic function

Some researchers also looked at whether AI-ECG methods could provide a more comprehensive risk assessment. One large study evaluating an AI-ECG platform (the AIRE) reported that it could estimate cardiovascular risk and mortality from standard 12-lead ECGs. Results from this platform were equal to or better than those obtained using traditional risk assessment methods (Sau et al., 2024). Other studies focused on how well diastolic dysfunction and short-term survival can be predicted in high-risk groups. In cardiac intensive care units (CICU), for instance, AI-ECG has been shown to give prognostic information that standard ECGs do not provide (Jentzer et al., 2025; Sau et al., 2024). The AIRE also broadens its use in prognostic applications by generating individualized survival estimates using discrete-time survival modeling and delivering personalized, time-dependent risk estimation (Sau et al., 2024).

Broader reviews

Several of the included articles were review papers that examined the current state of AI-ECG research. These articles highlighted not only the strengths of AI-ECG but also repeated problems, like poor standardization, limited external validation, and the problem of making AI results easy for clinicians to understand (Feeny et al., 2020; Nagarajan et al., 2021; Siontis et al., 2021; Muzammil et al., 2024; Dali et al., 2025).

Key findings

Across the studies included in this review, AI-based ECG interpretation repeatedly showed encouraging results:

- Arrhythmia detection was highly accurate, especially for atrial fibrillation — demonstrated in multiple studies using deep learning applied to 12-lead and single-lead ECGs (Hannun et al., 2019; Wu et al., 2021; Jabbour et al., 2024; Nagarajan et al., 2021).

- Detection of ischemia and myocardial infarction was often more effective than with traditional automated systems — especially in models trained on emergency-department or prehospital ECGs, including work on OMI detection and reducing false-positive STEMI activations (Goto et al., 2019; Lee et al., 2025; Dali et al., 2025).
- Heart failure and structural heart disease detectable from routine ECGs achieved an accuracy that may be useful in clinical practice, for example, for screening, as shown in studies detecting reduced ejection fraction, diastolic dysfunction, left atrial enlargement, and other forms of structural remodeling (Cho et al., 2024; Chou et al., 2024; Jentzer et al., 2025; Poterucha et al., 2025).
- Pulmonary hypertension and cardiotoxicity AI-ECG are still developing. Still, early findings of these areas of AI-ECG research look encouraging — with significant results in the early detection of pulmonary hypertension and prediction of treatment-related toxicity (DuBrock et al., 2024; Shaffer et al., 2024).

We summarized the major clinical applications and implications of AI-enabled ECG in a table (Table 2).

Table 2. Clinical applications of AI-enabled ECG and main implications

Clinical domain	Example applications	Potential clinical value	Key limitations
Arrhythmia detection	AF screening, occult AF detection, VPC identification	Early identification of arrhythmias, opportunistic screening	Predominantly retrospective datasets; limited external validation
Acute ischemia / myocardial infarction	AI-ECG triage in emergency departments	Faster recognition of high-risk patients, support of early decision-making	Variable reference standards; performance may differ across populations
Structural heart disease	Detection of cardiomyopathies, left atrial enlargement	Opportunistic identification of structural abnormalities	Dependence on echocardiographic labels; potential spectrum bias
Heart failure and diastolic dysfunction	Prediction of reduced EF, diastolic dysfunction, prognosis	Risk stratification, identification of high-risk patients	Heterogeneous definitions of HF and diastolic dysfunction
Pulmonary hypertension	Early detection from standard ECGs	Earlier referral and diagnostic work-up	Limited prospective validation
Cardiotoxicity and treatment-related risk	Prediction of AF or mortality in oncology/transplant patients	Monitoring of vulnerable populations	Small specialized cohorts
Cardiovascular risk profiling	Estimation of physiologic age, mortality, composite CV risk	Long-term risk stratification	Unclear impact on clinical decision-making

Relation to prior literature

Previous reviews have shown that AI-ECG could be useful for several heart conditions, like arrhythmia diagnosis, ischemia detection, structural heart disease, and risk stratification (Feeny et al., 2020; Siontis et al., 2021; Kashou et al., 2022). Our results are broadly consistent with those reviews, but they also underline the uneven quality of the scientific evidence. Many studies use small, retrospective, or single-center datasets, which may reduce performance when the models are tested in everyday clinical practice (Nagarajan et al., 2021; Muzammil et al., 2024). The transparency of these models remains problematic. Explainability tools such as saliency maps and feature attribution methods are increasingly used in AI-ECG work. Despite this, they often fail to provide explanations that clinicians find practical and easy to interpret, as noted in previous reviews (Siontis et al., 2021; Kashou et al., 2022).

Methodological concerns

Several recurring methodology problems came up repeatedly. They included, for example, datasets from a single center or narrow groups of patients, inconsistent definitions of outcomes, limited testing from the outside, class imbalance for rare conditions, and a lack of details about how the model was built and trained. Recent reviews of AI-ECG show that using good, diverse data, checking results carefully, and careful focus on ethical issues like bias and data privacy are the key for these tools to be safely used in daily care (Siontis et al., 2021; Feeny et al., 2020; Kashou et al., 2022; Muzammil et al., 2024). These issues make it difficult to compare models or judge how close they are to being usable in practice.

Clinical implications

AI-ECG systems could support clinicians in many practical situations such as providing quick and accurate arrhythmia screening (Hannun et al., 2019; Nagarajan et al., 2021; Wu et al., 2021), improving early recognition of ischemia (Goto et al., 2019; Lee et al., 2025; Dali et al., 2025), identifying patients with possible heart failure (Cho et al., 2024; Jentzer et al., 2025; Poterucha et al., 2025), monitoring high-risk populations for early signs of cardiotoxicity (Shaffer et al., 2024), and allowing remote check-ups using wearable ECG devices (Feeny et al., 2020; Siontis et al., 2021). Scientists have also recommended using AI-ECG in emergency departments to help manage cases of syncope. These tools can help identify ECG patterns associated with inherited irregular heartbeats or heart structure problems and use this information to improve the risk assessment (Thiruganasambandamoorthy et al., 2024). These uses of applications demonstrate how AI-ECG could change not only how well we diagnose patients but also patient flow and resource use in emergency care. Despite this potential, we should consider AI-ECG as a tool that complements clinical expertise rather than replaces it. Putting it into clinical practice demands rigorous validation, clear transparency, and a well-designed workflow (Kashou et al., 2022; Siontis et al., 2021).

Limitations of this review

This review has several important limitations. Because not all relevant AI-ECG studies were accessible and full-text availability differed, we didn't include several studies. Because the methods varied widely, a quantitative summary of the results was not possible, which is consistent with challenges described in prior methodological reviews of AI-ECG (Siontis et al., 2021; Feeny et al., 2020). Finally, because AI research evolves rapidly, newer studies may emerge after we complete the literature search.

4. CONCLUSION

AI-driven ECG interpretation is a rapidly developing field with significant clinical promise. Today's models can identify arrhythmias, ischemia, heart failure, structural problems, pulmonary hypertension, and cardiotoxicity caused by treatments. Most current studies are still in the early stages, use small datasets, and do not have strong external validation. This issue is often highlighted in the literature. In the future, researchers should focus on diverse, representative populations, clear and complete reporting, and prospective study designs. Understanding how AI-ECG tools influence clinical decisions and patient outcomes will be very important. With continued refinement and careful implementation, AI-ECG technology may enhance the diagnostic value of conventional ECGs and enable faster, more accurate patient care.

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Authors' Contributions

Anna Mazur: Conceptualization, methodology, writing – rough preparation, project administration
Julia Brodziak: Conceptualization, writing - review and editing, supervision
Wiktoria Ciszewska: Check, resources, visualization
Michał Dworak: Methodology, writing - review and editing
Katarzyna Fojcik: Software, investigation, data curation
Zofia Kosztyła-Czech: Formal analysis, data curation, visualization
Marta Kowalska: Software, resources, writing – rough preparation, Supervision
Mateusz Matyja: Check, writing - review and editing
Wiktor Werenkowicz: Data curation, investigation
Tomasz Wiśniewski: Formal analysis, investigation
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Informed consent

Not applicable.

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Conflict of interest
The authors declare that they have no conflicts of interest, competing financial interests or personal relationships that could have influenced the work reported in this paper.

Data and materials availability
All data associated with this study will be available based on reasonable request to the corresponding author.

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